

A Study on the Quantitative Evaluation Model for the Dissemination Effectiveness of Ideological and Political Discourse on Social Media Platforms

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ABSTRACT As social media has become a major channel for information dissemination, the communication path of ideological and political discourse has changed significantly. Scientifically evaluating dissemination effectiveness is essential for improving communication quality and optimizing discourse strategies. This study integrates communication effectiveness theory, ideological discourse characteristics, and social media dissemination patterns to construct a quantitative evaluation framework for ideological and political discourse on social media platforms. The framework includes five primary dimensions: dissemination breadth, dissemination depth, audience feedback, guidance effectiveness, and industry adaptability, which are further divided into 15 secondary indicators. A combination of the Analytic Hierarchy Process and entropy weighting is used to determine indicator weights, and a multidimensional comprehensive evaluation model is established. Empirical validation is conducted using cases from Douyin, WeChat Official Accounts, and specialized online platforms. The results show that the proposed model can effectively quantify dissemination effectiveness and provide methodological support for improving communication strategies, audience engagement, and discourse guidance in digital public communication environments.

INDEX TERMS social media, ideological discourse, communication effectiveness, quantitative evaluation, sentiment analysis

I. INTRODUCTION

AS a new communication paradigm, social media has accelerated information dissemination within social networks [1]. Social media, represented by platforms such as WeChat, QQ, Xiaohongshu, Weibo, Douyin, Bilibili, and Zhihu, has become a primary channel for the public to access information, express opinions, and exchange ideas. This transformation is largely attributed to its strong interactivity, rapid dissemination speed, and extensive reach. It also provides a new medium for the dissemination of ideological and political discourse, profoundly impacting the ideological and political education management system for university students [2]. The textile sector, as a traditional Chinese industry with distinct advantages, embodies intangible cultural heritage techniques, industrial heritage, and a meticulous craftsmanship ethos. These elements collectively serve as core components of ideological discourse [3]. The effectiveness of disseminating such discourse on social media directly impacts the textile industry. It determines the industry's ability to champion mainstream values, foster industrial consensus, and amplify its cultural influence. How-

ever, information dissemination on social media platforms differs significantly from traditional communication scenarios. It exhibits distinct characteristics such as fragmentation, decentralization, and personalization [4]. The dissemination of ideological and political discourse in the textile sector faces multiple challenges. Such discourse includes concepts of intangible cultural heritage preservation, green textile development initiatives, and stories of master craftsmen. These diverse dissemination pathways involve fragmented demands across textile industry practitioners, university teachers, and consumers. Traditional qualitative methods are insufficient to accurately measure the communication effectiveness of textile cultural discourse. This is particularly true amidst complex public sentiment feedback. Against this backdrop, constructing a scientific and systematic measurement and evaluation model is essential. Such a model can precisely quantify the dissemination effectiveness of ideological and political discourse in the textile sector on social media platforms. It enables an objective grasp of the current status and challenges in disseminating textile-related ideological discourse, providing data support for

optimizing communication strategies. Moreover, it enriches the theoretical framework for assessing the effectiveness of ideological and political communication in the textile industry. This approach promotes the deep integration of ideological and political work with textile industry development and new media technologies. It thereby aids the inheritance of textile intangible cultural heritage, facilitates the dissemination of green textile concepts, and cultivates the spirit of craftsmanship. This holds significant theoretical and practical value for advancing high-quality development in the textile industry [5].

II. RELATED RESEARCH

Early studies established foundational theoretical frameworks for evaluating communication effectiveness. These include Harold Lasswell's "5W" model which was proposed in 1948 by the then-Yale Law School professor, Hovland's persuasion theory, and the Uses and Gratifications Theory. Regarding social media communication effectiveness evaluation, researchers have primarily focused on dimensions such as information reach, user interaction behaviors, and public opinion evolution. They have employed econometric methods and network analysis to construct evaluation models [6]. However, these studies mainly target commercial information and public events. They rarely address the particularities of ideological and political discourse, and lack integration with specific industrial cultural contexts. Early studies on the communication effectiveness of ideological and political discourse centered on traditional media contexts. These studies primarily employed qualitative analysis to explore content construction and dissemination pathways. With the rise of social media, researchers began examining the dissemination of such discourse in new media environments. They also attempted to develop evaluation indicator systems [7]. However, existing research exhibits several shortcomings. First, indicator selection often emphasizes dissemination volume while neglecting dissemination quality and guidance effectiveness. Second, weighting determinations are highly subjective, lacking objective refinement. Third, model validation remains insufficient, limiting applicability. Fourth, specialized studies targeting specific industries—particularly textiles—are scarce. These studies fail to fully integrate industry-specific contexts such as textile intangible cultural heritage preservation and industrial upgrading. Furthermore, there is insufficient consideration of adaptability to professional content like industrial policies and industry standards. To this end, this study aims to develop a scientific, comprehensive, and operational quantitative evaluation model. The model is tailored to the development needs of the textile industry and its full industrial chain communication scenarios, such as production, trade, consumption. This approach seeks to address existing research gaps and provide practical support for ideological discourse dissemination in the textile sector.

III. RESEARCH APPROACH AND METHODOLOGY

The research approach for this study is illustrated in Figure 1. First, we systematize the relevant theoretical foundations. This helps clarify the core connotations and influencing factors of ideological and political discourse dissemination on social media platforms. Second, based on both theory and practice, we select evaluation indicators and construct a multidimensional evaluation system. Third, we combine the Analytic Hierarchy Process (AHP) and entropy weighting method. This allows us to determine indicator weights. Based on this, we establish a quantitative evaluation model. Finally, the model's scientific validity and practical feasibility are validated through empirical cases across multiple platforms and themes, with optimization recommendations proposed.

The research methodology is illustrated in Figure 2. First, the Delphi method was employed to invite experts from ideological and political education, communication studies, econometrics, and the textile industry. These experts screened and refined the evaluation indicators [8]. Second, the Analytic Hierarchy Process (AHP) and entropy weighting method were used. These methods determined indicator weights by comprehensively considering subjective and objective factors [9]. Third, empirical research was employed to validate the model. Representative cases of ideological discourse dissemination on social media platforms were used for this purpose. Comment text data were processed through sentiment analysis techniques (e.g., based on a finetuned BERT model) [10].

To ensure methodological transparency, the sentiment analysis procedure is detailed as follows. For the positive comment sentiment ratio (C2), sentiment orientation was identified using a BERT-based pre-trained model fine-tuned on a manually annotated corpus of 5,000 textile-related social media comments. Interannotator agreement (Cohen's $\kappa = 0.84$) was achieved through independent annotation by three researchers. The fine-tuned model achieved a macro-average F1-score of 0.87 on a held-out test set (precision: 0.88, recall: 0.86 for positive sentiment). Comments classified as neutral were excluded from the calculation, and the positive sentiment ratio was defined as: Positive Ratio = Positive Comments / (Positive + Negative Comments). This approach ensures that the indicator reflects genuinely favorable attitudes rather than neutral or technical observations. To address domain-specific language, the fine-tuning corpus included textile industry terminology (e.g., "pilling," "dyeing defects," "fabric strength") to reduce misclassification of constructive professional feedback as negative sentiment. Comments containing such technical observations without explicit emotional valence were classified as neutral and excluded from the positive ratio calculation. This domain-adaptive approach enhances the validity of sentiment analysis for textile-related content.

IV. QUANTITATIVE EVALUATION OF IDEOLOGICAL DISCOURSE DISSEMINATION ON SOCIAL MEDIA

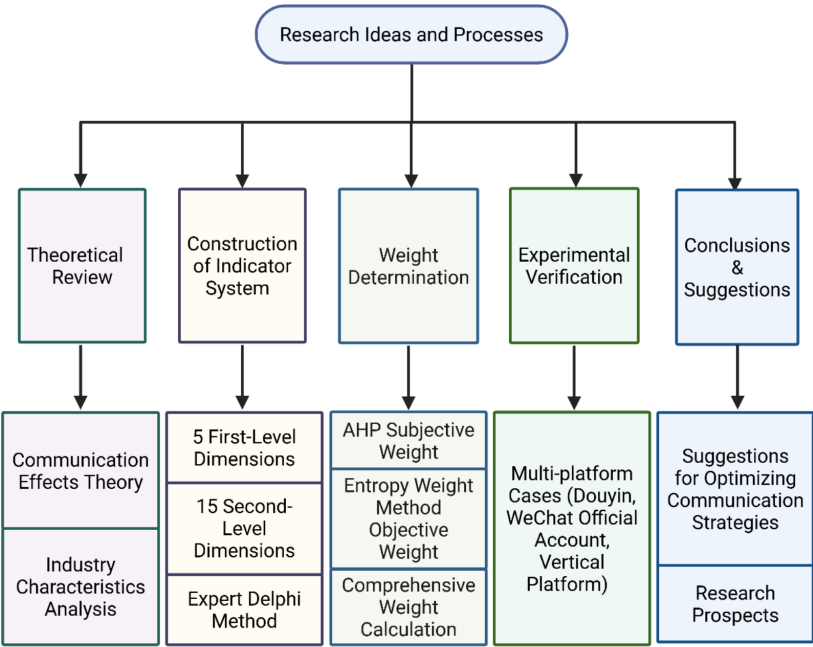


FIGURE 1. Research Approach and Technical Roadmap

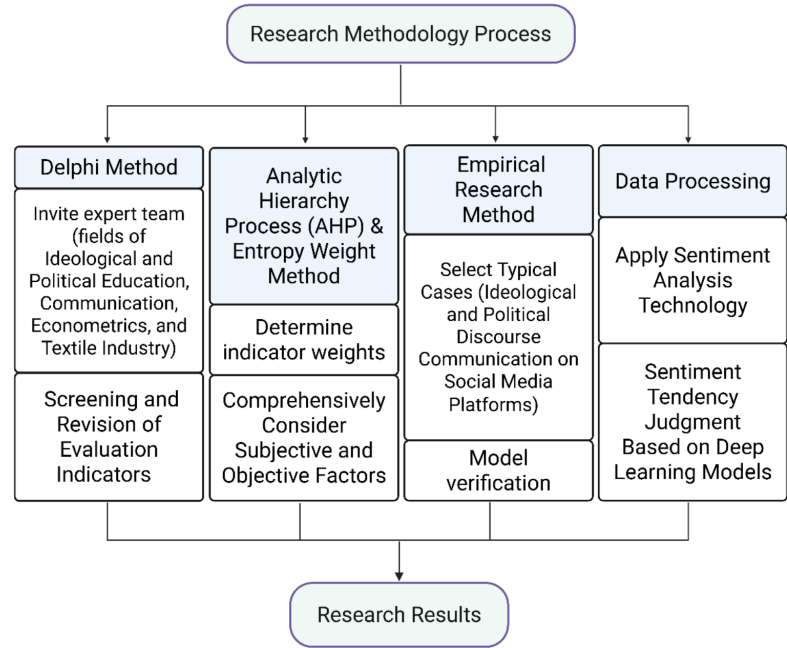


FIGURE 2. Research Methodology Framework (Delphi-AHP-Entropy Weighting Method-Empirical Verification)

A. PRINCIPLES FOR INDICATOR SELECTION

(1) Scientific Principle: Indicator selection should be grounded in relevant theories. This approach objectively and accurately reflects the core essence of ideological and political discourse dissemination effectiveness on social media platforms, while avoiding subjective speculation. (2)

Comprehensiveness Principle: The indicator system should encompass multiple dimensions including dissemination breadth, dissemination depth, audience feedback, guidance effectiveness, and industry adaptability. This enables comprehensive measurement of all aspects of dissemination effectiveness. (3) Operability Principle: Indicator data should

be readily obtainable through methods such as social media platform backend data, questionnaire surveys, content analysis, and public opinion monitoring. This ensures the practicality of the model. (4) Dynamic Principle: Considering the dynamic nature of the social media environment, the indicator system should possess flexibility and adaptability. This allows for adjustments based on evolving communication practices. (5) Industry-Specific Principle: Indicators should reflect the unique characteristics of the textile industry. They should embody core themes such as intangible cultural heritage preservation, green development, and craftsmanship spirit. Additionally, they should address communication needs across different stages including production, trade, and consumption [11].

B. CONSTRUCTION OF EVALUATION INDICATOR SYSTEM

This study constructs a quantitative evaluation indicator system for the dissemination effectiveness of ideological and political discourse on social media platforms. The system is based on the aforementioned principles and core concepts, while also incorporating expert opinions. As shown in Table 1, it comprises 5 primary indicators and 15 secondary indicators.

1) Dissemination Reach (A)

Measures the scope and coverage of such discourse communication, comprising three secondary indicators: (1) Total Views/Plays (A1): Refers to the cumulative number of times users viewed/watched ideological and political discourse content, reflecting basic information reach capability. (2) Forwarding/Sharing Volume (A2): The total number of times users actively forward/share ideological and political discourse content, reflecting the information's diffusion capacity and social influence. (3) Target Audience Coverage Rate (A3): The proportion of relevant target audiences (e.g., textile industry practitioners, university faculty and students) among reached users, reflecting the precision of dissemination.

2) Communication Depth (B)

Measures the audience's reception and comprehension of ideological discourse, comprising three secondary indicators: (1) Average dwell time/completion rate (B1): Refers to the average duration users spend browsing/ viewing ideological discourse content or the proportion of complete playbacks. Longer durations or higher completion rates indicate deeper engagement and understanding. (2) Content Key Information Mention Rate (B2): The frequency users mention core concepts and specialized terminology (e.g., "keesi silk weaving," "zerocarbon textiles") in comments, derivative works, etc., reflecting audience retention and internalization. (3) Deep Engagement Rate (B3): The proportion of comments sparking sustained discussions or multiple-round replies among total comments is calculated.

This proportion indicates the depth of reflection prompted by the content.

3) Audience Feedback (C)

Measures audience emotional attitudes and engagement toward ideological discourse, comprising three secondary indicators: (1) Like Rate (C1): The ratio of likes to views/play counts, reflecting general emotional resonance. (2) Positive Comment Sentiment Ratio (C2): Comment sentiment orientation is identified through sentiment analysis models (e.g., BERT-based pre-trained models). The proportion of positive sentiment comments is then calculated, reflecting audience attitude inclinations. (3) Bookmark Rate (C3): The ratio of bookmarks to views/play counts, reflecting the long-term value of content to audiences.

4) Guidance Effectiveness (D)

Measures the guiding role of ideological discourse on audience values and behaviors, comprising three secondary indicators: (1) Value Identification (D1): Audience identification with core values of ideological discourse in the textile sector (e.g., craftsmanship spirit, intangible cultural heritage preservation, green concepts) is quantified. This is achieved through questionnaire surveys (5-point Likert scale) or in-depth interviews. (2) Behavioral Intention Conversion Rate (D2): This metric measures the proportion of audiences developing specific positive behavioral intentions after receiving information. Such behaviors include learning intangible cultural heritage skills, purchasing eco-friendly textiles, and engaging in textile innovation. The assessment is conducted via questionnaires. (3) Public Sentiment Guidance Index (D3): This metric is calculated by analyzing shifts in sentiment orientation and key issue frameworks within relevant public discourse. Such analysis focuses on discussions before and after the release of ideological discourse (e.g., discussions on "textile pollution" or "disappearing intangible cultural heritage").

5) Industry Adaptability (E)

Measures the alignment of ideological discourse content with the characteristics and developmental needs of the textile industry, comprising three secondary indicators: (1) Professional Content Accuracy (E1): Industry experts evaluate the accuracy of content related to textile techniques, process standards, industrial policies, etc., within the ideological discourse. (2) Industry Scenario Alignment (E2): Assesses whether content covers and effectively connects to practical needs across diverse scenarios including textile production, R&D, trade, and consumption. (3) Policy Standard Relevance (E3): This metric analyzes the degree of association and interpretation between content and relevant policy frameworks. These include nationally and industrially issued textile development plans, green manufacturing standards, intangible cultural heritage protection policies, and related documents [12]. Consistent with this principle, the evaluation of E1 was conducted as follows. Industry

experts evaluate the accuracy of content related to textile techniques, process standards, and industrial policies. This introduces an element of expert judgment. However, such domain-specific validation is essential given the specialized nature of textile knowledge. Fully automated verification tools for such content are currently lacking. While E1 relies on expert judgment, its role is to ensure content validity for specialized industry knowledge, a function that current automated methods cannot fully replace.

V. A QUANTITATIVE MODEL FOR ASSESSING MESSAGE IMPACT DISSEMINATION

A. DETERMINING INDICATOR WEIGHTS: COMBINING AHP WITH ENTROPY WEIGHTING

The determination of indicator weights directly impacts the scientific rigor of the evaluation model. This study employs the Analytic Hierarchy Process (AHP) to establish subjective weights. It then combines these subjective weights with entropy weighting to determine objective weights. The comprehensive weights are obtained through weighted averaging, balancing expert experience with data objectivity.

1) Determining Subjective Weights (ω_{sub}) via AHP

A hierarchical structure model was constructed. Experts were invited to conduct pairwise comparisons, forming a judgment matrix. The eigenvector was calculated, and subjective weights were obtained after consistency testing. Subjective weights were derived using the Analytic Hierarchy Process (AHP) based on input from seven experts spanning four domains: ideological and political education, communication studies, econometrics, and the textile industry. This interdisciplinary composition ensures diverse perspectives in evaluating the indicator system. All pairwise comparison matrices met the consistency requirement ($CR < 0.1$), indicating reliable expert judgments. In AHP, the validity of weights depends primarily on the expertise and consistency of participants rather than sample size. The panel size used here aligns with common practice in multi-criteria evaluation studies.

2) Determining Objective Weights (ω_{obj}) via Entropy Weighting

Data from all secondary indicators were standardized. The information entropy of each indicator was calculated. Lower information entropy indicates greater discriminative power and higher weight for the indicator.

3) Calculation of Composite Weight (ω_{com})

To determine the composite weights, a weighted average method is employed: $\omega_{\text{com}} = \alpha \cdot \omega_{\text{sub}} + (1 - \alpha) \cdot \omega_{\text{obj}}$. The trade-off coefficient α reflects the relative importance assigned to subjective versus objective weights. Following expert consultation, α was set to 0.5, balancing theoretical insights from domain experts with empirical data distributions—a common practice in multi-criteria decision-making when no prior evidence suggests dominance of

either approach [13]. To test the robustness of this choice, a sensitivity analysis was conducted by varying α from 0.3 to 0.7. The comprehensive evaluation scores for the three cases remained stable. Their ranking order did not change, confirming that the model's conclusions are not sensitive to the specific value of α .

B. CONSTRUCTION OF QUANTITATIVE EVALUATION MODEL

Based on the established evaluation indicator system and determined comprehensive weights, a linear weighted summation method is employed. This method constructs a quantitative evaluation model for the dissemination effectiveness of the evaluation framework. The model formula is:

$$E = \sum (\omega_i \cdot X'_i) \quad (i = 1, 2, \dots, 15) \quad (1)$$

Where E represents the comprehensive score for the dissemination effectiveness of ideological and political discourse, ω_i denotes the comprehensive weight of the i -th secondary indicator, and X'_i indicates the standardized score of the i -th secondary indicator. To more intuitively reflect dissemination effectiveness levels, the comprehensive score E categorizes dissemination effectiveness into five grades: Excellent ($E \geq 85$), Good ($70 \leq E < 85$), Average ($55 \leq E < 70$), Poor ($40 \leq E < 55$), and Very Poor ($E < 40$).

C. MODEL DATA PROCESSING METHOD

All secondary indicators undergo standardization to eliminate dimensional differences. For positive indicators, the extreme value standardization method is applied: $X'_i = (X_i - X_{\min}) / (X_{\max} - X_{\min})$. All standardized scores fall within the range $[0, 1]$. For qualitative data such as sentiment analysis of comments, numerical scores are first derived via sentiment analysis models before standardization.

VI. EMPIRICAL ANALYSIS

Building on the evaluation indicator system and the composite weights derived from the AHP-entropy approach, this section applies the quantitative model to three representative cases. The objective is to test the model's applicability across diverse platform types and content formats, and to examine variations in dissemination performance across the five primary dimensions.

A. CASE SELECTION AND DATA COLLECTION

To validate the model's universality, this study selected three case types for multi-platform empirical analysis: (1) Case 1 (Douyin): Short video series "Textile Intangible Heritage Inheritance: Weaving Dreams with Craftsmanship". (2) Case 2 (WeChat Official Account): A series of posts titled "Frontiers of Green Textile Technology and Policy Interpretation" published by the official WeChat account of a textile industry association. (3) Case 3 (Textile Vertical Platform: "Textile Talent" App): A series of articles titled "Career Interviews with Master Craftsmen in China's Textile

TABLE 1. Evaluation Indicator System

Primary Indicator	Secondary Indicator	Description	Data Source
Reach (A)	A1: Total Views/Plays	Total number of content views/plays	Platform back-end
	A2: Shares/Reposts	Number of user-initiated shares	Platform back-end
	A3: Target Audience Reach	Percentage of target audience reached	Surveys/Audience Profiling
Engagement (B)	B1: Average dwell time/completion rate	User viewing duration/proportion of full plays	Platform back-end
	B2: Mention rate of key content messages	Number of times core messages mentioned in comments/secondary creations	Text analysis
	B3: Deep engagement rate	Proportion of comments triggering multiple rounds of replies	Comment analysis
Audience Feedback (C)	C1: Like rate	Ratio of likes to views	Platform back-end
	C2: Positive Sentiment Ratio in Comments	Proportion of comments with positive sentiment	Sentiment analysis
	C3: Bookmarking Rate	Bookmarks/Views ratio	Platform back-end
Guidance Effectiveness (D)	D1: Value Alignment	Audience alignment with core values	Survey
	D2: Behavioral Intent Conversion Rate	Proportion of users developing positive behavioral intent	Survey
	D3: Public Sentiment Guidance Index	Shift in sentiment orientation of relevant public discourse	Public sentiment monitoring
Industry Alignment (E)	E1: Professional Content Accuracy	Content professional accuracy score	Expert evaluation
	E2: Industry Scenario Fit	Degree of coverage across industrial chain scenarios	Expert assessment
	E3: Policy/Standard Relevance	Level of alignment with industry policies/standards	Content analysis

Industry". For Case 3 (Textile Talent App), platform metrics were obtained through direct collaboration with the platform operator, which provided aggregated analytics data for the published content series.

B. DATA COLLECTION METHODS

(1) Platform Data: Obtained metrics such as views, shares, dwell time, and comments via platform backends or public APIs (where available). (2) Questionnaire Survey: A total of 1,500 questionnaires were distributed across the three case platforms, with 1,382 valid responses collected (92.1% valid response rate). Stratified quota sampling was employed based on key demographic variables. These variables included occupation (textile practitioners, university students, consumers), age, and education level. This approach ensured balanced representation of target audiences. For each case, approximately 460 valid responses were obtained. This sample size met the minimum requirements for subgroup analysis in communication research. While this sampling approach enhances representativeness, potential selection bias remains a limitation, as noted in the limitations section. (3) Public Sentiment Data: Utilized public sentiment monitoring systems to collect data on relevant topics during each case's dissemination period. (4) Expert Scoring: Seven experts in textile technology, intangible cultural heritage research, and industrial economics conducted blind evaluations of case content, assessing professional accuracy (E1) and contextual relevance (E2). Platform backend data, including views, shares, average dwell time, and completion rates, were obtained through authorized access to the analytics dashboards of the content-publishing organizations. Specifically, data for the Douyin case were retrieved from Douyin's Creator Center, and data for the WeChat Official Account case were obtained via WeChat's Official Account Data Platform, both accessible to verified account holders. For metrics not directly available through these tools, such as completion rates for text-based content, alternative proxy indicators or survey-based methods were employed as indicated in Table

1. All data collection complied with platform terms of service and relevant data protection regulations. The same panel of seven experts covering ideological and political education, communication studies, econometrics, and the textile industry. Inter-rater reliability (Fleiss' $\kappa = 0.82$) indicated substantial agreement. Expert scores were cross-validated against documentary evidence, including official technical standards and industry policy documents, to ensure consistency.

C. INDICATOR WEIGHT CALCULATION

(1) Subjective Weight Calculation: Scores were obtained by inviting seven experts covering ideological and political education, communication studies, econometrics, and the textile industry. Subjective weights were then derived after passing consistency tests. (2) Objective Weight Calculation: Entropy weighting method weights were computed based on initial data from three cases (15 indicators $\times$ 3 cases = 45 groups). (3) Comprehensive Weight Calculation: Using $\alpha=0.5$, calculate the comprehensive weights for each secondary indicator (e.g., Target Audience Coverage A3=0.078, Content Key Information Mention Rate B2=0.081, Positive Comment Sentiment Ratio C2=0.085, Behavioral Intent Conversion Rate D2=0.088, Industry Scenario Alignment E2=0.083, etc.).

D. MODEL APPLICATION AND COMPARATIVE ANALYSIS OF RESULTS

After substituting the normalized data from each case into the model, the calculated results (Table 2) are as follows: (1) Case 1 (TikTok Short Video): Overall score E=76.8, rated "Good." It demonstrates strengths in dissemination breadth (A=80.1) and audience feedback (C=78.9), while showing relative weaknesses in industry adaptability (E=70.2) and guidance effectiveness (D=72.5), particularly with a low behavioral intention conversion rate. (2) Case 2 (WeChat Official Account Post): Overall score E=71.5, rated "Good." It excels in communication depth (B=75.6, high key in-

formation mention rate) and industry adaptability (E=77.3, strong policy relevance), but its communication breadth (A=68.4) is limited. (3) Case 3 (Vertical Platform Article): Overall score E=73.2, rated “Good.” It excels in guidance

effectiveness (D=76.8, high conversion rate of practitioners’ behavioral intent) and target audience reach (A3=0.79), but its public influence (dissemination breadth A=65.7) is relatively weak.

TABLE 2. Calculated Subjective-Objective Weights and Comprehensive Weights for 15 Secondary Indicators

Secondary Indicators	Subjective Weight (AHP)	Objective Weight (Entropy Weighting Method)	Comprehensive Weight
A1: Pageviews/Views	0.075	0.070	0.073
A2: Shares/Reposts	0.074	0.072	0.073
A3: Target Audience Reach	0.080	0.076	0.078
B1: Viewing Duration/Completion Rate	0.069	0.071	0.070
B2: Key Message Mention Rate	0.082	0.080	0.081
B3: Deep Engagement Rate	0.070	0.068	0.069
C1: Like Rate	0.065	0.067	0.066
C2: Positive Comment Ratio	0.084	0.086	0.085
C3: Save Rate	0.063	0.065	0.064
D1: Value Recognition Rate	0.076	0.078	0.077
D2: Behavioral Intent Conversion Rate	0.088	0.090	0.088
D3: Public Sentiment Guidance Index	0.072	0.074	0.073
E1: Content Accuracy	0.079	0.077	0.078
E2: Contextual Relevance	0.083	0.085	0.083
E3: Policy Alignment	0.080	0.081	0.081

As shown in Figure 3, short videos facilitate broader dissemination and emotional resonance, while in-depth articles excel in professional content assimilation and industry

behavior guidance. Significant audience differences across platforms necessitate differentiated dissemination strategies. The model effectively uncovers structural variations in the dissemination effectiveness of ideological discourse within the textile sector. These variations exist across different platforms and content formats.

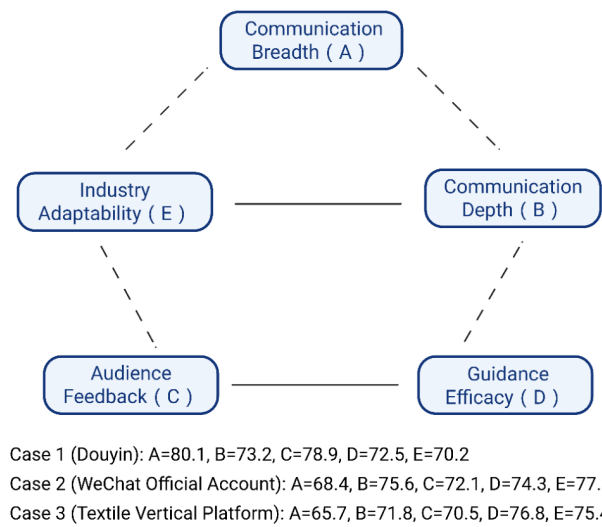


FIGURE 3. Radar Comparison of Communication Effectiveness Across Three Cases (Douyin vs. WeChat Official Accounts vs. Textile Vertical Platforms)

VII. CONCLUSIONS AND OUTLOOK

A. RESEARCH FINDINGS

This study developed a quantitative evaluation model. The model assesses the communication effectiveness of ideological discourse in the textile sector across social media platforms. The model incorporates fifteen indicators across five dimensions and demonstrated its validity through multi-platform empirical testing. This model not only quantifies dissemination effectiveness but also reveals the dynamic relationships among “reach,” “depth,” “feedback,” “efficacy,” and “industry adaptability.” Findings indicate that enhancing the dissemination effectiveness of ideological discourse in the textile sector should not solely pursue traffic volume. Instead, it requires optimizing content formats and dissemination strategies. This optimization should be based on platform characteristics and audience profiles. Content professionalism and industry relevance must also be ensured. By doing so, effective guidance from value recognition to behavioral transformation can be achieved. Findings indicate that enhancing the dissemination effectiveness of ideological discourse in the textile sector should not solely pursue traffic volume. Instead, it requires optimizing content formats and dissemination strategies based on platform characteristics and audience profiles. At the same time, content professionalism and industry relevance must be ensured. The results also reveal positive correlations between value recognition and behavioral intention. This provides preliminary evidence consistent with the hypothesized pathway from cognitive

acceptance to behavioral transformation.

B. POLICY RECOMMENDATIONS (FIGURE 4)

(1) Implement a “Platform-Content-Audience” Precision Matching Strategy: Customize content formats according to platform characteristics (e.g., Douyin emphasizes visuals, WeChat prioritizes depth, vertical platforms focus on expertise) and utilize user profiling for targeted delivery. (2) Deepen the integration of “professional content + ideological core”: Collaborate with industry experts, intangible cultural heritage inheritors, and model craftsmen to co-create content. Organically weave industry policies, technical standards, and craft processes into narratives to enhance industry adaptability (E) and communication depth (B). (3) Design an “Online Resonance-Offline Action” linkage mechanism: Online interest and identification can be stimulated through topic challenges, virtual experiences, and knowledge quizzes. These online engagements can then be connected to offline activities such as skill training, product experiences, and factory tours to drive behavioral conversion (D2). (4) Establish a “dynamic monitoring-real-time feedback” closed-loop optimization mechanism: Using this research model as the foundational framework, integrate big data dashboards to conduct real-time monitoring and early warning of key indicators. This enables dynamic adjustments to communication strategies.

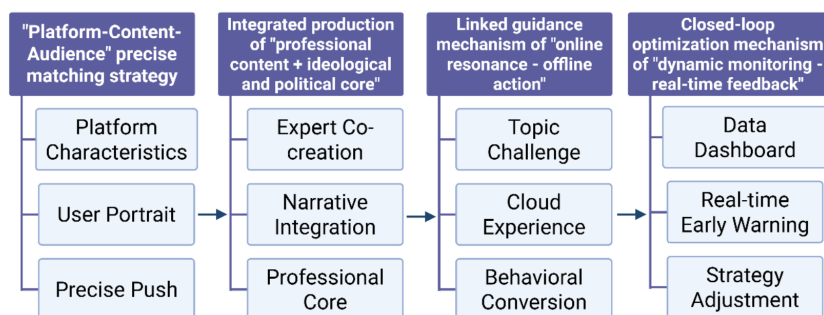


FIGURE 4. Framework for Optimizing Ideological and Political Discourse Dissemination in the Textile Sector

C. RESEARCH LIMITATIONS AND FUTURE DIRECTIONS

This study has certain limitations: First, the data collection period was relatively short, and the cross-sectional design does not permit causal inferences regarding the temporal process from value recognition to behavioral transformation. Future research should therefore employ longitudinal designs to track dynamic changes in dissemination effects. Second, although the sentiment analysis model achieved high accuracy, misjudgments remain possible. Third, it did not fully cover all types of social media platforms (e.g., overseas platforms, emerging video channels). Fourth, indicator E1 (professional content accuracy) relies on expert

evaluation, which, while cross-validated, introduces a degree of subjectivity. Future research may explore automated content verification approaches, such as knowledge graph-based fact-checking, to further enhance objectivity. Future research may explore the following directions: (1) Develop a dynamic long-term evaluation model: Incorporate time-series data to assess the long-term decay and sustained impact of dissemination effects, establishing a dynamic evaluation framework. (2) Deepen research on algorithmic influence mechanisms: Investigate how platform recommendation algorithms affect the visibility of ideological discourse in the textile sector and drive audience homogeneity/ heterogeneity. (3) Expand

cross-cultural comparative studies: Examine the dissemination effectiveness and cross-cultural adaptation strategies of China's textile-related ideological discourse (e.g., textile intangible cultural heritage, green standards) on overseas social media platforms [14]. (4) Explore applications of intelligent evaluation technologies: Investigate utilizing natural language processing to automatically extract content expertise. Additionally, employ computer vision to analyze the relationship between video content and audience attention, thereby enhancing the automation and intelligence of evaluation processes [15].

AUTHOR CONTRIBUTIONS

Rui Sheng designed, collected and analyzed the data, and drafted the manuscript. Rui Sheng conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Rui Sheng participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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